

# Causal Relationship between the Volatility of Stock Market and Selected Macroeconomic Variables: Case of Malaysia

*(Hubungan Sebab Penyebab antara Kemeruapan Pasaran Saham dan Kemeruapan Makroekonomi Terpilih: Kes Malaysia)*

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## ABSTRACT

*This study examines the dynamic relationship between the volatility of stock market and macroeconomics' volatility in Malaysia during the period of February 1991 to February 2013. For this purpose, monthly data on the KLCI stock index and a set of macroeconomic variables are used. Firstly, in order to estimate the volatility of each series, the well-known GARCH family models are employed. The empirical stylized facts in the stock indices and the macroeconomic variables are presented. Secondly, in order to investigate the causation between variables, the Toda and Yamamoto causality test through a VAR method is conducted using the volatility of stock market and macroeconomic variables. In addition, from the VAR, we generate Impulse Response Function and Variance Decomposition to track the evolution of economic shocks through the system. The result of this study shows that exchange rate volatility affects Malaysian stock market volatility considerably. Furthermore, trade openness is able to affect stock market volatility in Malaysia. These results will provide more precise information for investors, hedgers, managers and policy makers.*

**Keywords:** *Stock market volatility; macroeconomic volatility; vector autoregressive model; Impulse response function; variance decomposition.*

## ABSTRAK

*Kajian ini meneliti hubungan dinamik antara kemeruapan pasaran saham dan kemeruapan makroekonomi di Malaysia bagi tempoh Februari 1991 hingga Februari 2013. Untuk tujuan tersebut, kajian ini menggunakan data bulanan Indeks Komposit Kuala Lumpur (KLCI) dan beberapa pemboleh ubah makroekonomi. Pertama, model GARCH digunakan bagi menganggar kemeruapan bagi setiap siri data yang seterusnya memperlihatkan fakta empirikal bagi indeks saham dan pemboleh ubah makroekonomi. Kedua, ujian sebab- penyebab Toda dan Yamamoto melalui kaedah vektor autoregresif (VAR) dilaksanakan bagi menguji hubungan sebab akibat antara kedua-dua pemboleh ubah kemeruapan pasaran saham dan kemeruapan makroekonomi. Seterusnya melalui kaedah fungsi tindakbalas impuls dan Dekomposisi Varians, kesan kejutan dalam ekonomi dapat dilihat terhadap kedua-dua pemboleh ubah tersebut. Hasil kajian ini mendapati kemeruapan kadar pertukaran mata wang asing sangat mempengaruhi kemeruapan pasaran saham Malaysia. Di samping itu keterbukaan dagangan juga didapati mampu mempengaruhi kemeruapan pasaran saham Malaysia. Hasil kajian ini memberikan maklumat yang lebih terperinci mengenai penentu kepada kemeruapan pasaran saham di Malaysia yang mana sangat berguna dalam pembuatan keputusan oleh para pelabur, pelindung nilai, pengurus dan pembuat polisi.*

**Kata kunci:** *Kemeruapan pasaran saham; kemeruapan makroekonomi; model vektor autoregresif; fungsi tindakbalas; dekomposisi varians.*

## INTRODUCTION

It can be safely stated that stock market volatility is a prominent factor in the economic growth in both developed and developing economies (Oseni and Nwosa 2011). Volatility, which is the standard deviation or

variance of stock returns, is often used as a basic measure of total risk of financial assets (Brooks, 2008). Financial markets play a significant role in the economic growth and development by assisting saving and transferring funds from savers to investors. Stock market volatility may harm the smooth working of the financial system

and therefore affect the economic performance and growth negatively (Merton and Bodie 1995; Mala and Reddy 2007).

In this regard, a question arises: What drives the stock market volatility? Several theoretical and empirical discussions in the finance literatures indicate that macroeconomic variables may affect stock market volatility. In the theoretical debates, multifactor asset pricing model is a main theory that supports the relationship between stock market and macroeconomic variables. Furthermore, the issue has been the subject of some empirical studies. In a seminal paper, Schwert (1989) found limited evidences of the existence relationship between stock market volatility and macroeconomic activity. However, the subsequent studies found more evidence in the existence of such relationship (relevant empirical studies are presented in literature review). If macroeconomic fluctuations exert more volatility to the stock markets, it leads to increase the risk and instability in economies. Therefore finding the determinant factors of stock market volatility would help to economic stability. Figure 1 provides some visual evidences of cyclical properties for volatility of stock market in Malaysia. It draws stock market volatility alongside GDP growth. A strict affiliation is observed between stock market volatility and the macroeconomic activity in Malaysia. The volatility of stock market is clearly higher during recessions, which emphasizes on the significant effect of the macroeconomic activity on the stock market volatility in Malaysia.

Although there exists a large body of studies about the effect of macroeconomic variables on stock price and stock return (first moment); the number of studies which investigate the issue for stock market volatility (second moment) is still limited especially for Malaysia. To have sufficient knowledge on the strength and degree of relationship between stock market volatility and macroeconomic variables provides important information in financial markets. Besides, it is so useful for portfolio decision, asset allocation and risk-management and helps to economic stability.

This study seeks to contribute to the existing studies by investigating the linkage between stock market volatility and macroeconomic volatility in the case of Malaysia. To do so, this study utilizes the Toda and Yamamoto causality test, Impulse Response Function and Variance Decomposition analysis. With

the purpose to examine the volatility of stock market and macroeconomic variables, this study uses the well-known GARCH models that are appropriate for time varying series. A VAR model is adopted to assess the causal relationship between variables. Utilizing the causality test, it is possible to examine if the past value of macroeconomic volatility can explain the current value of stock market volatility. However, the sign of effect and the duration of shocks' influence can be investigated by Impulse response function and Variance decomposition.

The results of this paper show that exchange rate volatility has significant roles in the fluctuation of stock market in Malaysia. The rest of this paper is organized as follows; Section 2 provides the empirical literatures in the subject of this study. Section 3 discusses on the data and methodology used in the present study. Section 4 describes the data and empirical results. Lastly, the conclusion is provided in section 5.

## LITERATURE REVIEW

In a seminal paper, Schwert (1989) tries to find some potential explanation for the time varying stock return volatility. One possibility that he considers is the probability of existence some relationship between stock market volatility and macroeconomic variables. Although his findings do not illustrate any strong relationship between macroeconomic activity and stock market volatility, subsequent studies have been found more evidence in such relationship. For instance, Liljeblom and Stenius (1997) find a robust linkage between conditional macroeconomic volatility and conditional stock market volatility in Finland. Their results indicate that one-sixth to above two-thirds of the variations in aggregate stock market volatility might be explained by macroeconomic volatility. In another related study, Mohamad and Wan Mahmood (2001) reveal that the absolute and squared return value of the exchange rate affect stock market volatility significantly. Sadorsky (2003) finds that macroeconomic volatility is extremely important to determine the volatility of technology stock price in the US. Moreover, Beltratti and Morana (2006) observe a bilateral linkage between stock market volatility and the volatility of macroeconomic variables, namely industrial production, the consumer price index and the Federal funds rate and M1 growth,

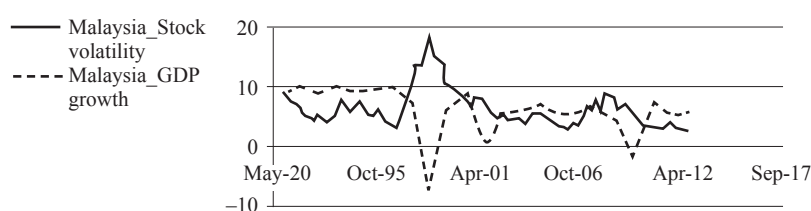


FIGURE 1. Stock market volatility and economic condition in Malaysia

Note: Data concerning stock market volatility and GDP growth are obtained from Data Stream

while causality is stronger from the macroeconomic variables to the stock market. Engle, Ghysels and Sohn (2006) report a strong unidirectional causality effect from macroeconomic volatility to stock market volatility in a mixed data sampling using GARCH-Midas method. Mun (2007) reports that higher exchange rate fluctuation causes higher stock market volatility in the UK, Italy, Australia, Japan and Singapore, but such relation was not significant in Germany, France and Hong Kong. According to Saryal (2007), the inflation rate affects stock market volatility strongly in Turkey. Although, such effect is not so strong in the case of Canada, it is still significant. Mala and Reddy (2007) find a statistical significant relationship between stock market volatility and interest rates in 16 firms in Fiji. Engle and Rangel (2008) show that stock market volatility can be influenced significantly by macroeconomic volatility in a sample including 50 developed and emerging countries. They introduce Spline-GARCH model to estimate the volatility of low frequency sampling. Furthermore, they conduct a panel approach and the Seemingly Unrelated Regressions (SUR) model to estimate the effect of macroeconomic volatility on stock market volatility in a large sample of 50 countries including all developed countries and most of the emerging markets. According to their results, the volatility of the stock market is influenced positively by the volatility of inflation, interest rate and real GDP. Instead of focusing upon high-frequency data, Diebold and Yilmaz (2008) investigate the relationship between stock market volatility and macroeconomic volatility based upon the volatility at medium (e.g. business cycle) frequencies. They find a unidirectional causal effect running from GDP volatility to stock market volatility.

Wang (2010) utilizes a two-step procedure to investigate the linkage between stock market volatility and macroeconomic volatility in China. Firstly, EGARCH model is used to examine the volatility of stock market and macroeconomic variables. Secondly, he utilizes the lag-augmented VAR (LA-VAR) model to analyze the causal relationships between stock market volatility and macroeconomic volatility. The results show that no significant causal effect exists from macroeconomic volatility to the stock market volatility. However, a causal effect running from stock market volatility to interest rate is observed.

In a similar manner and in a two-step procedure, Oseni and Nwosa (2011) apply AR-EGARCH model and lag augmented VAR Granger causality to analyze the relationship between stock market volatility and macroeconomic volatility in Nigeria. They find a bi-directional causal relationship between stock market volatility and GDP volatility. However, no evidence of causality between stock market volatility and the volatility of interest rate and inflation is found.

Walid et al. (2011) show that exchange rate changes exert a significant effect on stock market volatility in four emerging countries, namely Singapore, Hong Kong,

Mexico and Malaysia. Recently, Beetsma and Giuliodori (2012) explore the linkage between GDP growth and stock market volatility in the US using a VAR model, impulse response function and forecast variance decomposition analysis. The results indicate that an increase in the stock market volatility declines the GDP growth in the US.

Among the literature, a limited number of studies utilize causality analysis, Impulse Response Function (IRF) and Variance Decomposition (VCD) analysis to investigate the relationship between stock market volatility and macroeconomic volatility. Using those analyses is important to investigate the issue because the regression analysis only indicates the association between series; however, the causal analysis determines the direction of the relationship between variables (Gujarati and Porter 2009). Therefore, the causality analysis is required to find which macroeconomic variables affect the stock market volatility. On the other hand, causality analysis is not enough to explain such relationship because as stated by Brooks (2008), it does not show the sign of the effect or how long the effect works through the system. Such information is provided by Impulse Response Function and Variance Decomposition analyses.

## DATA AND METHODOLOGY

### DATA

The goal of the present study is to examine the causal relationship, if any, between stock market volatility and macroeconomic volatility in Malaysia. To do so, the present study utilizes the Kuala Lumpur Composite Index (KLCI) and a set of macroeconomic variables including consumer price index (CPI), Real Effective Exchange rate (EX), interest rate (INT), Industrial production index (IPI), Money supply (M) and Trade openness (OPEN). The Malaysia Klibor One Month - Offered Rate is used as INT. We use monthly data that cover the period of February 1991 to February 2013. The Census X12 method is used to adjust the effect of seasonal fluctuation on macroeconomic variables. All data are collected from Thomson Reuters Data Stream.

Trade openness is measured by  $(Export + Import)/GDP$ . This measurement is in the line with practice in the literature (e.g., Giovanni and Levchenko 2008; Kim et al. 2010; Hadad et al. 2012). Since the available data in trade openness only cover the frequency more than quarterly, the frequency conversion method is applied to the openness series to achieve the monthly series (the frequency conversion is applied by Eviews software and using linear-Match last method. In this method, each value in the low frequency series is assigned to the last high frequency observation related to the low frequency period, then all intermediate points on straight lines are placed connecting these points. For more information regarding the frequency conversion method, see Doran

(1974); Pavia-Miralles (2010); Denk and Weber (2011)). The continuously compounded returns formula is employed to calculate the return of series as follows,

$$r_t = \ln P_t - \ln P_{t-1}$$

where  $r_t$  is the return at time  $t$ ,  $\ln$  is the natural logarithm,  $P_t$  is the current monthly price and  $P_{t-1}$  is previous month's price for stock and macroeconomic series.

#### VOLATILITY MODEL

In order to achieve the goal of this study, a two-step approach is employed in the line with Morelli (2002). In the first step, this study adopts the well-known ARCH (autoregressive conditional heteroskedasticity) model introduced by Engle (1982) and developed by Bollerslve (1986) as GARCH (Generalized ARCH) model to obtain the conditional volatility of stock market and macroeconomic variables. The AR ( $p$ )-GARCH ( $p, q$ ) model can be expressed as

$$r_t = \mu + \sum_{i=1}^p a_i r_{t-i} + \varepsilon_t \quad (1)$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i} \quad (2)$$

Equation (1) represents the mean equation where  $r_t$  is the return at time  $t$  and  $\varepsilon_t | I_{t-1}$  denotes the error term regarding the information in time  $t-1$ .  $\varepsilon_t$  is normally distributed. Equation (2) shows the variance equation as  $h_t$  is the conditional variance of return series at time  $t$ . (Beside GARCH model, the exponential GARCH model that is an extension of GARCH models is adequately sufficient model for the some series in this study).

The variance equation for univariate GARCH (1,1) model can be expressed as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (3)$$

Many extensions of GARCH models exist, however the present study employs two extensions of GARCH models, namely exponential GARCH (EGARCH) and the GARCH-in-mean (GARCH-M).

The exponential GARCH (EGARCH) model extended by Nelson (1991) allows for asymmetric effects between positive and negative asset returns by considering the weighted innovation and using the log of conditional variance in the model. The EGARCH ( $p, q$ ) model is shown as,

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^q a_i g(z_{t-i}) + \sum_{i=1}^p \beta_i \ln \sigma_{t-i}^2 \quad (4)$$

Where  $z_t = \varepsilon_t / \sigma_t$  which conveys the asymmetric effect of positive and negative shocks in the EGARCH model.

An EGARCH (1,1) model can be expressed as follows:

$$\begin{aligned} \ln \sigma_t^2 &= \alpha_0 + a_1 g(z_{t-1}) + \beta_1 \ln \sigma_{t-1}^2 \\ &= \alpha_0 + \lambda \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2 \end{aligned} \quad (5)$$

Furthermore, it is possible in the financial time series that the return of an asset depends on its volatility. To model such behavior, Engle and Bollerslev (1986) introduced GARCH-M model. The return equation in a GARCH(1,1)-M model can be expressed as follows:

$$r_t = \mu + c\sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2) \quad (6)$$

where  $c$  is referred to as the risk premium. When  $c$  is positive and statistically significant, then the return is positively related to its volatility.

#### VECTOR AUTOREGRESSIVE (VAR) ANALYSIS

In the second step of this study, we adopt a VAR model to assess causal relationship between stock market volatility and macroeconomic volatility. Furthermore, VAR method enables to assess dynamic responses of stock market volatility to macroeconomic volatility as well as to assess the Forecast Error Variance decomposition of stock market volatility.

Vector autoregressive (VAR) method is suggested by Sims (1980). A VAR model is a set of regressions that contains more than one dependent variable. In each regression, the current value of each variable depends on its own lagged value and the lagged value of other variables. A VAR system including  $g$  variables,  $y_{1t}, y_{2t}, \dots, y_{gt}$ , can be expressed as,

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \dots + \beta_k y_{t-k} + \mu_t \quad (7)$$

(g×1) (g×1) (g×g)(g×1)(g×g)(g×1) (g×g)(g×1)(g×1)

VAR method has an advantage over the univariate methods so that it is not necessary to identify which variables are endogenous or exogenous. This is important since the extant theories are uncertain about which variables should be regarded as exogenous variable, which creates difficulties for researchers to classify the variables (Brooks 2008).

The most common way to investigate the causal relationship between series is the Granger Causality test introduced by Granger (1969) and then modified slightly by Sims (1972). The Granger-causality test has been used to find any correlation between the current value of a time series and the past values of others (Brooks 2008). The Granger causality test for the present study involves the system of equations in the VAR method as follows,

$$\begin{aligned} h_{Mt} &= \omega_0 + \sum_{i=1}^p \phi_i h_{Mt-i} + \sum_{j=1}^5 \sum_{i=1}^p \theta_i h_{MVjt-i} \\ &\quad + \sum_{i=1}^p \vartheta_i OPEN_{t-i} + \varepsilon_t \end{aligned} \quad (8)$$

Where  $h_{Mt}$  is defined as the conditional volatility of stock market at time  $t$ ,  $h_{MVjt-i}$  is the conditional volatility in the  $j$ 'th macroeconomic variable at time  $t-i$  for  $i = 1, \dots, p$ .  $P$  is the optimal lag length which is determined by Akaike information criteria. The existence of causal linkage between variables is determined by F-test.



However, the Granger causality test has some limitations. As shown by Park and Phillips (1989) and later by Sims, Stock, and Watson (1990), when the series are integrated, the result of VAR model and F-test are not valid. Toda and Yamamoto (1995) propose a procedure requiring the estimation of an augmented VAR which is robust to the integration properties of the process. Following Toda and Yamamoto (1995), the present study uses a system of equation in the lag augmented VAR method which is specified as,

$$h_{Mt} = \omega_0 + \sum_{i=1}^{p+d_{max}} \phi_i h_{Mt-i} + \sum_{j=1}^5 \sum_{i=1}^{p+d_{max}} \theta_{ij} h_{MVjt-i} + \sum_{i=1}^{p+d_{max}} \vartheta_i OPEN_{t-1} + \varepsilon_t \quad (9)$$

Where  $d_{max}$  is the maximal order of integration which is suspected to occur in the system. All the other variables are as previously defined. The present study utilizes the ADF, PP and KPSS unit root tests to determine the maximum order of integration ( $d_{max}$ ) in the system. The proposed method by Toda and Yamamoto (1995) is applicable even if the series are stationary.

#### IMPULSE RESPONSE FUNCTION (IRF) AND VARIANCE DECOMPOSITION (VCD)

Although by using Granger causality test it is possible to find which variable affects the future value of the other variables in the system, it does not show the sign of the relation and how long the effects require to take place. Such information is given by Impulse response function and Variance decomposition (Brooks 2008).

Consider a bivariate vector autoregressive model,

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (10)$$

The moving average representation of equation (10) can be written as follows,

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y} \\ \bar{z} \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \Theta_{11}(i) & \Theta_{12}(i) \\ \Theta_{21}(i) & \Theta_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{yt-i} \\ \varepsilon_{zt-i} \end{bmatrix} \quad (11)$$

The set of coefficients in equation (10) (i.e.,  $\Theta_{11}(i)$ ,  $\Theta_{12}(i)$ ,  $\Theta_{21}(i)$  and  $\Theta_{22}(i)$ ) are referred to IRFs. An impulse response function measures the time profile of the effect of shocks at a given point in time on the (expected) future values of variables in a dynamical system.

For a VAR system including  $g$  variables,  $g^2$  impulse responses are generated. If the VAR model includes a large number of variables and lags, it is difficult to observe the impact of shocks to the system. In this case, to show the interactions between the series, VDC analysis or 'forecast error variance decomposition' can be applied.

The following equation represents the  $n$ -step-ahead forecast error variance of  $y_{t+n}$ .

$$\begin{aligned} \sigma_y(n)^2 &= \sigma_y^2[\Theta_{11}(0)^2 + \Theta_{11}(1)^2 + \dots + \Theta_{11}(n-1)^2] \\ &= \sigma_z^2[\Theta_{12}(0)^2 + \Theta_{12}(1)^2 + \dots + \Theta_{12}(n-1)^2] \end{aligned} \quad (12)$$

The  $n$ -step-ahead forecast error variance can be decomposed into proportions due to shocks in  $\varepsilon_{yt}$  and  $\varepsilon_{zt}$ , respectively, as follows:

$$\frac{\sigma_y^2[\Theta_{11}(0)^2 + \Theta_{11}(1)^2 + \dots + \Theta_{11}(n-1)^2]}{\sigma_y(n)^2} \quad (13)$$

and

$$\frac{\sigma_z^2[\Theta_{12}(0)^2 + \Theta_{12}(1)^2 + \dots + \Theta_{12}(n-1)^2]}{\sigma_y(n)^2} \quad (14)$$

The forecast error variance decompositions give the proportion of the movements in a series that are due to its own shocks versus shocks to the other variables. A shock from each variable will not only affect that variable, but will also transmit the shock to all other variables in the VAR system (Enders, 2010).

## EMPIRICAL RESULT

This section provides the empirical findings regarding the stylized facts, GARCH family estimation, the unit root test for the estimated volatility, the Granger causality analysis and lastly, the result of Impulse Response Function and Variance decomposition approaches.

Table 1 provides descriptive statistics for return series in stock market and macroeconomic variables. The mean of return series ranges between -0.2686 and 1.0482 which the lowest mean return is related to interest rate with negative value and the highest mean return accounts for money supply. The return of stock market (KLCI) shows the highest standard deviation among series. All series show positive excess kurtosis which means that their distributions are fatter than normal. The negative value of skewness for the return of KLCI, exchange rate, and interest rate indicates longer left side tail than right side in their distribution. Conversely, positive skew for CPI, IPI and money supply demonstrates that the right side of their return distribution is longer than left side. The Jarque-Bera normality test shows that all return series are not normally distributed.

The existence of unit root in return series are investigated by Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The results indicate that all return series are stationary at 1% level.

Table 2 presents the results of fitted GARCH family models to the desired return series including the return of stock market and macroeconomic variables. Akaike information criterion, Schwartz criterion, log likelihood values and Ljung-Box statistics are utilized for choosing adequate models. The comparisons between deferent kind of GARCH models which leads to find adequate GARCH model for each variable are provided in the tables 6-11 in the appendix. It is found that GARCH(1,1) for stock return, EGARCH(1,1) for exchange rate,

TABLE 1. Descriptive statistics for return series

	Return of					
	KLCI	EX	INT	CPI	IPI	M
Mean	0.4093	0.0408	-0.2686	0.2292	0.4363	1.0482
Maximum	26.654	15.561	16.454	3.8899	14.640	5.7852
Minimum	-34.410	-21.247	-2.636	-1.2036	-13.540	-2.5147
Std. dev.	6.8251	2.5212	5.0060	0.3866	4.9474	1.3416
Skewness	-0.2426	-0.4406	-3.2295	3.2318	0.1541	0.5527
Kurtosis	7.0821	28.337	27.226	32.310	3.6666	3.7609
Jarque-Bera	193.64	7338.3	7203.2	10247.3	6.1144	20.485
Probability	0.0000	0.0000	0.0000	0.0000	0.0470	0.0000
Q(12)	26.992***	16.551	67.331***	36.591***	165.72***	38.813***
Q <sup>2</sup> (12)	194.64***	117.66***	32.134***	9.257	62.775***	34.832***
ADF	-14.03***	-15.19***	-8.22***	-12.80***	-4.31***	-14.35***
PP	-14.01***	-15.26***	-12.53***	-12.82***	-31.12***	-14.35***
KPSS	0.043	0.096	0.049	0.072	0.048	0.127*

ADF indicates Augmented Dickey-Fuller test under null hypothesis of existence of unit root. PP is indicates Phillips-Perron unit root test under the null hypothesis of existence unit root. Including intercept and trend, the critical values for ADF test and PP test are -3.99(1%), -3.42(5%), -3.13(10%). KPSS is Kwiatkowski-Phillips-Schmidt-Shin unit root test under the null hypothesis of being stationary. Including intercept and trend, the critical values of KPSS test are 0.216(1%), 0.146(5%) and 0.119(10%). Q(12) and Q<sup>2</sup>(12) distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. In table 1, \*\*\* and \* indicate significant at 1% and 10% respectively.

TABLE 2. GARCH model and diagnostic tests

		Log-likelihood	Box-Ljung	
			Q(12)	Q <sup>2</sup> (12)
Stock market	GARCH(1,1)	-860.6384	16.499	20.522
Exchange rate	EGARCH(1,1)	-525.2562	17.339	5.9991
Interest rate	AR(1)-GARCH(1,1)	-407.2552	7.7987	1.4633
Consumer price index	ARCH(1)	-55.15561	21.420	6.375
Industrial production index	AR(2)-ARCH(1)	-644.1135	15.139	5.482
Money supply	AR(3)-EGARCH(1,1)	-374.4345	9.514	7.409

Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  under the null hypothesis of no autocorrelation with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively.

AR(1)-GARCH(1,1) for interest rate, ARCH(1) for consumer price index, AR(2)-ARCH(1) for industrial production index and AR(3)-EGARCH(1,1) for money supply are adequately fitted models for volatility. Besides, GARCH-M models conducted to all series for detect the existence of GARCH in mean but this model is not found to improve the fitted GARCH. Ljung-Box statistics (Q(12) and Q<sup>2</sup>(12)) show that there is no serial correlations up to lag 12 indicating that the mean and variance equations are well fitted.

Table 3 shows the result of unit root test for trade openness and the volatilities obtained from GARCH family. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests confirm that the volatility of exchange rate, interest rate, consumer price index, money supply and industrial production index are stationary at level. Trade openness is not stationary by ADF, PP and KPSS. While

the volatility of KLCI is stationary by KPSS, the result of ADF and PP tests indicate that KLCI volatility is not stationary at level. Therefore, the result of unit root tests for KLCI volatility is inconclusive. The result of ADF, PP and KPSS unit root tests at first deference shows that OPEN and KLCI volatility are I(1). Hence, one extra lag ( $d_{max} = 1$ ) is added to the optimal lag of VAR model for implementing the Granger causality test using Toda and Yamamoto (1995) approach.

The Toda and Yamamoto causality test through a vector autoregressive (VAR) model is employed to analyze the relationship between the volatility of stock market and macroeconomic variables. The related empirical results are shown in table 4. It is found that among all macroeconomic variables, only exchange rate volatility causes stock market volatility in Malaysia. However, it is detected that KLCI volatility causes the volatility of exchange rate, interest rate, consumer price index

TABLE 3. Unit root test

Level	ADF	PP	KPSS
OPEN	-1.78	-1.50	0.454***
Volatility of:			
KLCI	-2.54	-2.34	0.132
EX	-5.53***	-5.63***	0.087
INT	-8.21***	-8.25***	0.101
CPI	-15.93***	-15.92***	0.067
M	-5.90***	-5.74***	0.091
IPI	-10.99***	-10.91***	0.094
First difference	ADF	PP	KPSS
OPEN	-4.84***	-6.41***	0.042
Volatility of KLCI	-18.43***	-18.56***	0.049

ADF indicates Augmented Dickey-Fuller test under null hypothesis of existence of unit root. PP indicates Phillips-Perron unit root test under the null hypothesis of existence unit root. Including intercept and trend, the critical values for ADF test and PP test are -3.99(1%), -3.42(5%), -3.13(10%). KPSS is Kwiatkowski-Phillips-Schmidt-Shin unit root test under the null hypothesis of being stationary. Including intercept and trend, the critical values of KPSS test are 0.216(1%), 0.146(5%) and 0.119(10%). In table 3, \*\*\* indicates significant at 1%.

and industrial production index. The feedback pattern (bidirectional-causality) can be detected only between the volatility of KLCI and exchange rate.

Figure 2 depicts the response of stock market volatility to macroeconomic volatility. The response of KLCI volatility to the exchange rate volatility is positive and significant. Although the response to exchange rate volatility shows a decline after fifth month but it increases again and reaches to it's maximum around 14<sup>th</sup> month. The response of KLCI volatility to the shocks from INT volatility and CPI volatility does not seem to be significant. The response of KLCI volatility to the industrial production index volatility is short and dies away before 10 months. In response to the money supply volatility and trade openness, KLCI volatility responses positively. The response to the money supply increases gradually and is felt with a short lag. The response of KLCI volatility to trade openness is increasingly with a decline after 6 months.

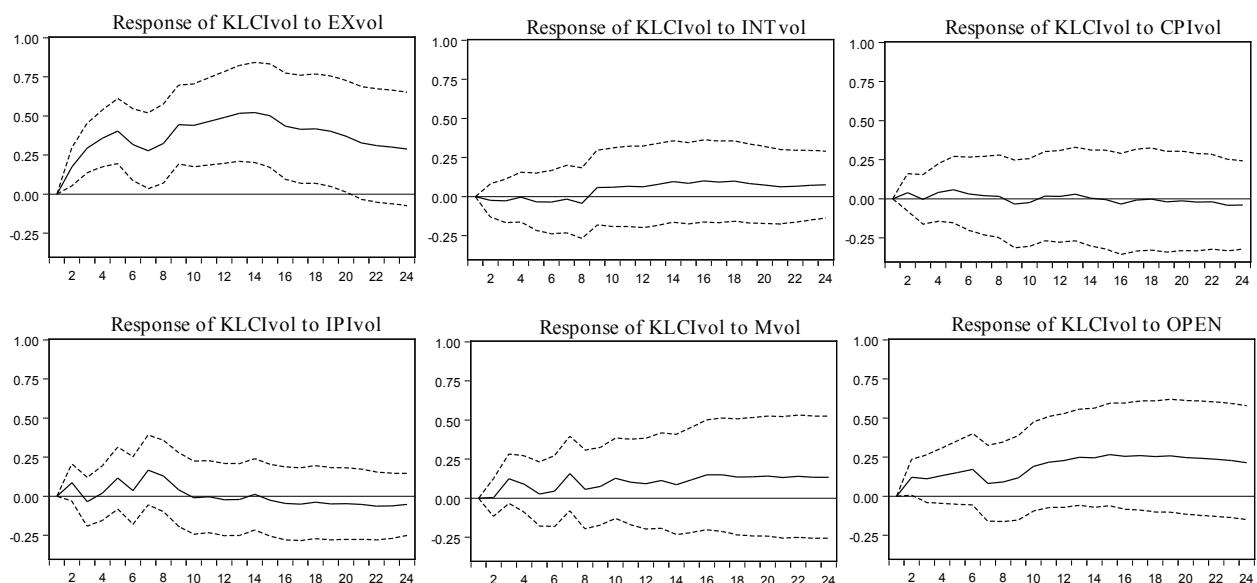
Table 5 provides the forecast error variance of KLCI volatility to macroeconomic shocks. The aggregate

TABLE 4. Toda and Yamamoto Causality test through VAR method

	EX	INT	CPI	IPI	M	OPEN
Predictive power of macroeconomic volatility	24.786*** EXvol→KLCIvol	5.165	3.53	13.56	9.21	9.82
Predictive power of stock market volatility	20.56** KLCIvol→EXvol	28.18*** KLCIvol→INTvol	18.28** KLCIvol→CPI vol	17.86** KLCIvol→IPIvol	10.32	16.30* KLCIvol→OPEN
Feedback effect	KLCIvol↔EXvol					

Table 4 presents  $\chi^2$  statistics for Wald test. The critical values of  $\chi^2$  (9) are 21.66, 16.91 and 14.68 at 1%, 5% and 10% respectively. \*, \*\* and \*\*\* indicate the significant causal relationship at 1%, 5% and 10% respectively. "→" shows the direction of causal relationship. "↔" indicates the existence of bidirectional causal relationship, supposing the feedback hypothesis.

#### Response to Cholesky One S.D. Innovations $\pm 2$ S.E.



In figure 2, "vol" denotes volatility.

FIGURE 2. Response of KLCI volatility to macroeconomic volatility

TABLE 5. Variance decomposition of KLCI volatility

Period	KLCIvol	Exvol	INTvol	CPIvol	IPIvol	Mvol	OPEN
1	100.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	95.89446	2.485405	0.006655	0.040779	0.534848	2.29E-05	1.037831
3	90.31620	6.673224	0.014681	0.031738	0.467006	0.894169	1.602985
6	81.66349	13.95785	0.028432	0.185498	0.893308	0.748538	2.522891
12	71.04661	22.24997	0.304636	0.181174	1.355806	1.193232	3.547028
18	65.78476	25.34527	0.625085	0.227637	0.977862	1.150866	5.854243
20	64.87852	25.65836	0.695636	0.304770	0.930531	1.124993	6.388064
24	63.92848	25.72655	0.848160	0.484117	0.893215	1.095492	7.023993

results are consistent with the Impulse Response Function patterns. The results of variance decomposition further support the significant effect of exchange rate on stock market volatility. The results show that after 24 months the exchange rate shocks account for more than 25 percent of stock market volatility. It is also affirmed by variance decompositions that the volatility of INT and CPI do not explain significantly the forecast error variance in stock market volatility significantly. After 24 months, only 0.84% and 0.48% of variation in KLCI volatility are attributed to the volatility of INT and CPI respectively. Similarly, only about 0.8% of forecast error variance in KLCI volatility can be explained by IPI volatility after 24 months. Moreover, the results indicate that about 1% of fluctuation in KLCI volatility is attributed to money supply volatility after 24 months. Variance decomposition indicates that trade openness is able to explain more than 7% of forecast error variance in stock market volatility after 24 months.

### CONCLUSION

This study examines the dynamic relationship between stock market volatility and macroeconomic volatility in Malaysia. Monthly data are employed on a set of macroeconomic variables and Kuala Lumpur Composite Index (KLCI). The volatility of each series is estimated by the GARCH models and the dynamic relationship is investigated by conducting the VAR method using the volatility of stock market and macroeconomic variables. The result indicates that among the six macroeconomic variables considered in this study, the volatility of exchange rate causes the volatility of KLCI. This result is consistent with the results of IRF and VDC which indicate that exchange rate volatility explains a significant amount of variation in KLCI volatility.

The findings of the present study provide preliminary insights about the risk elements for fund managers and investors to understand the linkage between macroeconomic volatility and the risk in stock market to make better investment decisions. It is also useful for hedgers in risk forecasting and developing hedging

strategies. Furthermore, such results may be helpful for policy makers monitoring the stability of financial markets so that the results provide useful insights for implementation and formulation macroeconomic policies to achieve financial stability. Because the stock market volatility is linked to some macroeconomic volatility, the weakness in the macroeconomic policies may be transmitted to stock market. Hence, it is advisable for those concerned on the development in the economic and stock market to heed the fluctuations of the EX and IPI.

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## APPENDIX

TABLE 6. Estimated GARCH models for KLCI

Fitted model	Adequate GARCH model				
	GARCH(1,1) Normal distribution	GARCH(1,1)-M Normal distribution	EGARCH(1,1) Normal distribution	GARCH(1,1) t distribution	GARCH(1,1) GED distribution
<u>Mean equation</u>					
$\mu$	0.606(0.0556)	0.457(0.3158)	0.498(0.1127)	0.790(0.0055)	0.845(0.0029)
c	–	0.006(0.6345)	–	–	–
<u>Variance equation</u>					
$\alpha_0$	1.067(0.0590)	1.076(0.0617)	–0.092(0.2093)	1.049(0.1551)	1.004(0.1682)
$\alpha_1$	0.174(0.0000)	0.177(0.0000)	–	0.187(0.0061)	0.178(0.0043)
$\beta_1$	0.802(0.0000)	0.799(0.0000)	0.950(0.0000)	0.796(0.0000)	0.802(0.0000)
$\lambda$	–	–	0.338(0.0000)	–	–
$\gamma$	–	–	–0.045(0.1885)	–	–
Log-likelihood	–865.0727	–864.9275	–866.8926	–860.6384	–860.7533
AIC	6.320529	6.326745	6.341037	6.295552	6.296388
SBC	6.373136	6.392505	6.406796	6.361311	6.362147
Q(12)	16.770(0.158)	17.252(0.140)	16.995(0.150)	16.499(0.169)	16.547(0.167)
Q <sup>2</sup> (12)	21.360(0.045)	21.751(0.040)	20.885(0.052)	20.522(0.058)	20.824(0.053)

The numbers in the parentheses show the  $p$ -value. Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. AIC indicates Akaike information criterion. SBC indicates Schwarz information criterion. The coefficients in the mean and variance equations are previously defined in equations 3, 5 and 6.

TABLE 7. Estimated GARCH models for EX

Fitted model	Adequate GARCH model				
	GARCH(1,1) Normal distribution	GARCH(1,1)-M Normal distribution	EGARCH(1,1) Normal distribution	EGARCH(1,1) t distribution	EGARCH(1,1) GED distribution
<u>Mean equation</u>					
$\mu$	–0.182(0.0746)	–0.188(0.1140)	–0.142(0.1761)	–0.080(0.2357)	–0.019(0.6993)
c	–	0.002(0.9202)	–	–	–
<u>Variance equation</u>					
$\alpha_0$	0.767(0.0000)	0.764(0.0000)	0.008(0.8918)	–0.078(0.4303)	–0.086(0.3347)
$\alpha_1$	0.314(0.0000)	0.314(0.0000)	–	–	–
$\beta_1$	0.480(0.0000)	0.482(0.0000)	0.758(0.0000)	0.858(0.0000)	0.840(0.0000)
$\lambda$	–	–	0.328(0.0000)	0.438(0.0102)	0.383(0.0035)
$\gamma$	–	–	0.329(0.0000)	0.196(0.0510)	0.209(0.0335)
Log-likelihood	–530.6693	–530.6660	–525.2562	–497.9126	–495.9157
AIC	3.902695	3.909971	3.870483	3.678194	3.663618
SBC	3.955442	3.975904	3.936416	3.757314	3.742738
Q(12)	18.885(0.091)	18.796(0.094)	17.339(0.137)	19.517(0.077)	19.744(0.072)
Q <sup>2</sup> (12)	7.3314(0.835)	7.3229(0.836)	5.9991(0.916)	4.1604(0.980)	4.1170(0.981)

The numbers in the parentheses show the  $p$ -value. Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. AIC indicates Akaike information criterion. SBC indicates Schwarz information criterion. The coefficients in the mean and variance equations are previously defined in equations 3, 5 and 6.

TABLE 8. Estimated GARCH models for INT

Fitted model	Adequate GARCH model					
	GARCH(1,1) Normal distribution	GARCH(1,1)-M Normal distribution	EGARCH(1,1) Normal distribution	AR(1)- GARCH(1,1) Normal distribution	AR(1)- GARCH(1,1) t distribution	AR(1)- GARCH(1,1) GED distribution
<u>Mean equation</u>						
$\mu$	0.058(0.3727)	-0.017(0.7843)	-0.325(0.0000)	-0.003(0.9889)	-8.83E-5(0.9976)	1.81E-06(0.9989)
AR(1)	—	—	—	0.461(0.0000)	0.208(0.0011)	0.196(0.0000)
c	—	-0.005(0.0550)	—	—	—	—
<u>Variance equation</u>						
$\alpha_0$	2.365(0.0000)	2.383(0.0000)	-0.088(0.0002)	2.319(0.0000)	0.003(0.9555)	0.107(0.0834)
$\alpha_1$	2.249(0.0000)	2.375(0.0000)	—	1.427(0.0000)	105.732(0.9563)	5.650(0.0015)
$\beta_1$	0.206(0.0000)	0.183(0.0000)	0.919(0.0000)	0.275(0.0000)	0.219(0.0000)	0.209(0.0000)
$\lambda$	—	—	0.585(0.0000)	—	—	—
$\gamma$	—	—	-0.272(0.0000)	—	—	—
Log-likelihood	-722.4641	-719.7438	-697.8707	-711.4120	-461.7761	-407.2552
AIC	5.283375	5.270864	5.111787	5.229285	3.414424	3.016462
SBC	5.335983	5.336624	5.177546	5.295218	3.493544	3.095581
Q(12)	29.679(0.003)	29.538(0.003)	37.454(0.000)	14.259(0.219)	0.3541(1.000)	7.7987(0.731)
Q <sup>2</sup> (12)	5.0464(0.956)	5.3608(0.945)	4.4657(0.973)	4.2476(0.962)	0.0893(1.000)	1.4633(1.000)

The numbers in the parentheses show the  $p$ -value. Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. AIC indicates Akaike information criterion. SBC indicates Schwarz information criterion. The coefficients in the mean and variance equations are previously defined in equations 3, 5 and 6.

TABLE 9. Estimated GARCH models for CPI

Fitted model	Adequate GARCH model			
	GARCH(1,1) Normal distribution	ARCH(1) Normal distribution	ARCH(1) t distribution	ARCH(1) GED distribution
<u>Mean equation</u>				
$\mu$	0.217(0.0000)	0.192(0.0000)	0.183(0.0000)	0.189(0.0000)
<u>Variance equation</u>				
$\alpha_0$	0.082(0.0000)	0.063(0.0000)	0.082(0.0004)	0.069(0.0000)
$\alpha_1$	0.810(0.0000)	0.747(0.0000)	0.440(0.0135)	0.498(0.0006)
$\beta_1$	-0.064(0.0000)	—	—	—
Log-likelihood	-80.49705	-82.89016	-55.15561	-57.14744
AIC	0.619026	0.629232	0.433374	0.447967
SBC	0.671912	0.668896	0.486260	0.500853
Q(12)	21.594(0.042)	20.675(0.055)	21.420(0.045)	21.184(0.048)
Q <sup>2</sup> (12)	5.3373(0.946)	6.4087(0.894)	6.3750(0.896)	6.2521(0.903)

The numbers in the parentheses show the  $p$ -value. Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. AIC indicates Akaike information criterion. SBC indicates Schwarz information criterion. The coefficients in the

mean and variance equations are previously defined in equations 3, 5 and 6.

TABLE 10. Estimated GARCH models for IPI

Fitted model	Adequate GARCH model				
	GARCH(1,1) Normal distribution	ARCH(1) Normal distribution	AR(2)-ARCH(1) Normal distribution	AR(2)-ARCH(1) t distribution	AR(2)-ARCH(1) GED distribution
<u>Mean equation</u>					
$\mu$	0.582(0.0000)	0.578(0.0000)	0.552(0.0000)	0.545(0.0000)	0.535(0.0000)
AR(1)	—	—	−0.441(0.0000)	−0.432(0.0000)	−0.442(0.0000)
AR(2)	—	—	−0.199(0.0006)	−0.188(0.0010)	−0.192(0.0008)
<u>Variance equation</u>					
$\alpha_0$	4.993(0.0000)	4.717(0.0000)	3.966(0.0000)	3.937(0.0000)	3.929(0.0000)
$\alpha_1$	0.578(0.0001)	0.575(0.0001)	0.579(0.0000)	0.593(0.0004)	0.590(0.0003)
$\beta_1$	−0.032(0.7380)	—	—	—	—
Log-likelihood	−671.6476	−671.8131	−644.1135	−643.4388	−643.4556
AIC	4.967997	4.961861	4.808248	4.810658	4.810782
SBC	5.021024	5.001631	4.874885	4.890623	4.890747
Q (12)	51.269(0.000)	51.306(0.000)	15.139(0.127)	15.235(0.124)	15.042(0.131)
Q <sup>2</sup> (12)	5.7141(0.930)	6.3473(0.898)	5.4820(0.857)	5.3960(0.863)	5.5066(0.855)

The numbers in the parentheses show the  $p$ -value. Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. AIC indicates Akaike information criterion. SBC indicates Schwarz information criterion. The coefficients in the mean and variance equations are previously defined in equations 3, 5 and 6.

TABLE 11. Estimated GARCH models for M

Fitted model	Adequate GARCH model					
	GARCH(1,1) Normal distribution	GARCH(1,1)-M Normal distribution	EGARCH(1,1) Normal distribution	AR(3)- EGARCH(1,1) Normal distribution	AR(3)- EGARCH(1,1) t distribution	AR(3)- EGARCH(1,1) GED distribution
<u>Mean equation</u>						
$\mu$	0.961(0.0000)	0.826(0.0000)	0.958(0.0000)	1.011(0.0000)	1.009(0.0000)	1.024(0.0000)
AR(1)	—	—	—	—	—	—
AR(2)	—	—	—	0.118(0.0462)	0.129(0.0273)	0.132(0.0219)
AR(3)	—	—	—	0.230(0.0002)	0.222(0.0002)	0.223(0.0001)
c	—	0.124(0.4087)	—	—	—	—
<u>Variance equation</u>						
$\alpha_0$	0.501(0.0082)	0.532(0.0035)	−0.241(0.0160)	−0.165(0.0348)	−0.169(0.0608)	−0.164(0.0769)
$\alpha_1$	0.303(0.0030)	0.316(0.0028)	—	—	—	—
$\beta_1$	0.271(0.2047)	0.231(0.2466)	0.676(0.0000)	0.791(0.0000)	0.785(0.0000)	0.790(0.0000)
$\lambda$	—	—	0.301(0.0122)	0.186(0.0473)	0.190(0.0780)	0.187(0.0945)
$\gamma$	—	—	0.228(0.0015)	0.210(0.0045)	0.210(0.0099)	0.212(0.0148)
Log-likelihood	−395.5143	−394.9273	−390.1422	−374.4345	−373.4141	−373.0256
AIC	2.926845	2.929870	2.894815	2.825441	2.825290	2.822412
SBC	2.979731	2.995978	2.960922	2.918733	2.931910	2.929032
Q(12)	45.570(0.000)	42.185(0.000)	43.749(0.000)	9.5148(0.484)	9.5334(0.482)	9.5386(0.482)
Q <sup>2</sup> (12)	4.3374(0.977)	4.1781(0.980)	4.5192(0.972)	7.4096(0.686)	7.3427(0.693)	7.2669(0.700)

The numbers in the parentheses show the  $p$ -value. Q(12) and Q<sup>2</sup>(12) are distributed as  $\chi^2(12)$  with the critical value of 26.217, 21.0261 and 18.5494 at 1%, 5% and 10% respectively. AIC indicates Akaike information criterion. SBC indicates Schwarz information criterion. The coefficients in the mean and variance equations are previously defined in equations 3, 5 and 6.